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Incorporating Neuroscience Data into Agent-Based Simulation Models of Buyer Behavior

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Abstract:

Purpose: *The article aims to analyze the possibility of using various cognitive neuroscience techniques when building the agent model of buyer behavior and propose an experimental procedure for obtaining qualitative data based on the triangulation of methods.*
Design/Methodology/Approach: *The proposed approach combines agent-based simulation with cognitive neuroscience techniques at the stage of designing the characteristics and behavior rules of agents-consumers.*
Findings: *The consumer's purchasing behavior is determined by the compilation of the influence of environmental factors and marketing stimuli as well as by his personality traits. Due to the necessity to consider all these elements when mapping the consumer-agent characteristics and decision rules, traditional methods of data collection may not be sufficient. In such a situation, cognitive neuroscience techniques can become a source of additional information, allowing to take into account the influence of emotions or cognitive abilities on one's decisions. To make it possible, it is necessary to conduct experiments with the use of neuroscience research tools (e.g., EEG, GSR, HR etc.) aimed at detecting emotional and cognitive states during exposure to an advertisement of a specific product. The neurophysiological data collected during the experiments allow for a more accurate estimation of the qualitative parameters describing consumer behavior rules.*
Practical Implications: *The proposed concept allows for a more accurate representation of agents-consumers' features and decision rules. Consequently, the agent-based model more reliably reflects reality, and thus the results obtained during model simulation are more valuable and can be the basis for formulating marketing plans.*
Originality/Value: *The proposed approach enriches the methodology of data collection and estimation of qualitative parameters in building agent models of buyer behavior.*

Keywords: *agent-based simulation, cognitive neuroscience, buying behavior*

JEL codes: *C63, C80, C90, D87, M37.*

Paper type: *Research article.*

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1. Introduction

An agent-based simulation is a relatively new approach to modeling complex systems, consisting of many interacting independent units, the so-called agents. The macro-scale image of the system under investigation is created by combining agents' actions and their interactions with each other and with the environment in which they function. In the last 20 years, this approach has gained considerable popularity in marketing research, with particular emphasis on consumer behavior research, as evidenced by the growing number of scientific publications in this field every year. A review of the Science-Direct database articles shows a considerable increase in this number over the last 15 years, from 3 in 2000 to 224 in 2020 (as of November 8, 2020).

Building an agent-based simulation model is not a simple task. The most common approach is a "bottom-up" that considers relevant actors and decisions at the micro-level that can produce a visible result at the system level (Grimm *et al.*, 2005). Therefore, the use of agent-based simulation requires that the created model reliably reflects interactions between agents and their behavior rules. This requirement raises an essential question regarding available empirical approaches to capturing information about agent behavior and their relative reliability (Robinson *et al.*, 2007).

In the case of agent-based models used to study the effects of purchasing decisions, a significant role is played by information resulting from the consumer's behavior, which is determined by the compilation of the impact on his awareness of environmental factors and marketing stimuli. Certain personality traits of the consumer are also influenced by four basic mental processes: motivation, perception, learning and remembering (Kotler and Keller, 2012). The need to consider all these factors when mapping the consumer-agent characteristics and decision rules means that traditional methods of gathering information may not be enough. As a consequence, the built agent model may not reflect reality with the required accuracy. Therefore, the question arises, is it possible to use additional methods in the data collection process that would complement and/or authenticate information collected traditionally?

In this article, the authors hypothesize that cognitive neuroscience can provide the appropriate techniques that allow obtaining additional information in the process of defining the rules of behavior of the consumer-agent and its interaction with the environment. Therefore, the article aims to analyze the possibilities of using various cognitive neuroscience techniques when building an agent-based model and propose an experimental procedure for obtaining qualitative data in this context, based on the triangulation of methods.

The article presents the essence of agent-based simulation and its application directions in marketing research. It discusses the basic techniques of cognitive neuroscience in the context of the possibility of their application to collect data required to map agents-consumers' behavior. Moreover, the concept of the procedure for obtaining data from various sources was presented to estimate the qualitative parameters of a specific agent-based simulation model of buyer behavior.

2. Agent-Based Simulation in Marketing Research

The origins of the agent-based simulation are derived from the theory of cellular automata, which, in a form that could be understood by computers, was developed independently by S. Ulam and J. von Neumann in the 1940s. However, it was not until the early 1970s that the agent-based simulation began to take shape as it is known today, thanks to J. Conway, who developed the game of life (Gardner, 1970).

The present understanding of the term "agent" appeared in 1991 (Holland and Miller, 1991), although various disciplines developed their definitions of this concept. It is commonly accepted that agents (which may be people, objects, ideas, institutions, or organisms) are placed in a specific environment and can act autonomously. Hierarchical structures are also possible in which a single agent belonging to a particular class may consist of multiple agents belonging to another class (Bonabeau, 2002; Epstein, 2006; Nava Guerrero *et al.*, 2016).

From a practical point of view, it can be assumed that the agent has the following properties (Macal and North, 2014, p. 15): (1) it is an identifiable entity with a certain set of features and rules governing its behavior and decision-making abilities; (2) it is located in an environment where it interacts with other agents; (3) its operation can be aimed at achieving a specific goal; (4) it is autonomous, it can function independently in its environment and in contacts with other agents, at least in certain defined situations; (5) is flexible, has the ability to learn and adapt.

The agent-based model does not have a fixed structure because the agents' decisions shape and change its state and structure. Decision-making processes are described on a micro scale for each agent individually. Through collective interaction between multiple agents and the environment in which they function, a macro-scale phenomenon emerges (Siebers and Aickelin, 2008). In other words, the agent-based approach essentially focuses on interactions at the micro-level that can explain emerg-ing patterns at the system level (Martin and Schlüter, 2015).

These assumptions predestine the agent-based simulation to be used in marketing research, as it may show how aggregated marketing phenomena arise from the actions of many agents identifying individual and/or organizational consumers.

In the last 20 years, many scientific studies have been published presenting cases of using agent-based simulation in this area. They very often refer to consumer behavior in the context of diffusion of innovation, for example, Shaikh *et al.* (2005), Watts and Dodds (2007), Rahmandad and Sterman (2008), Goldenberg *et al.* (2009), Delre *et al.* (2010) and Stummer *et al.* (2015). Another application direction relates to market acceptance research (Goldenberg *et al.*, 2007; 2010). Many publications present the use of the agent-based approach in the analysis of the impact of company positioning on consumer behavior (Wilkinson and Young, 2002; Tay and Lusch, 2004; 2005; Meng *et al.*, 2017), while some focus on the problem of moral behavior in relational marketing (Midgley *et al.*, 2006; Hill and Watkins, 2007; 2009).

Another important area of application of the agent-based approach concerns the study of purchasing trends in specific markets by simulating many individual consumers' choices to determine how and why consumers choose a given product or service. Applications of this type are discussed in Twomey and Cadman (2002), Robertson (2003), Schenk *et al.* (2007), Ulbinaitė and Moullec (2010), Kuhn *et al.* (2010) and Fikar *et al.* (2019).

Some studies present more general considerations on the agent approach in the study of consumer behavior, for example, Janssen and Jager (2003), Jager (2006) and Roozmanda *et al.* (2011). They describe agent-based models of consumer behavior derived from the theory of marketing and behavioral sciences and then show the results of several simulation experiments conducted based on real data from a specific market.

3. Premises and Possibilities of Using the Cognitive Neuroscience Techniques

Most of the agent-based models aim to simulate some real-life phenomena and are therefore designed and verified based on data collected from the socio-economic world. However, the basic requirement is that the models show structural and behavioral similarity to the original system. When designing agents, this means that they must be constructed in a manner similar to their real counterparts in terms of structure and behavior. For example, when an agent is to map a human-consumer and his decisions, it must be equipped with all the properties and behavior patterns of a real human important in the scenarios studied. (Kennedy, 2011; Crooks *et al.*, 2018).

In this case, when constructing the model, traditional methods of collecting qualitative data may not be enough, such as, for example, focus groups, in-depth interviews, participant observations, desk research, or ethnographic research (Janssen and Ostrom, 2006; Robinson *et al.*, 2007; Ghorbani *et al.,* 2015) because they have significant limitations - they are subjective, difficult to reproduce and not representative for a larger population (Daymon and Holloway, 2011). Quantitative data collection methods can help address these problems, such as the commonly used self-report questionnaires (Gordon and Ciorciari, 2017), measuring and evaluating opinions, feelings, attitudes and behaviors (French and Ross, 2019). They can facilitate understanding of the study population (Basil, 2017) and be the basis for defining agent behavior rules. Still, people often do not tell us precisely what they really think or do (Neeley and Cronley, 2004). This means that this type of research will never give us a complete picture of their minds.

Modeling human behavior in agent-based simulation, especially in terms of decision-making in various conditions and determining the probability of making a specific choice, is challenging because it is difficult to capture all human personality and behavior nuances. To simplify this task, one uses an approach that focuses only on the features relevant to the correctness of a given model (Crooks *et al.,* 2018). Typically, two types of behavioral frameworks are used for this purpose – mathematical or cognitive (Kennedy, 2011; Balke and Gilbert, 2014). In mathematical models, however, it is assumed that decisions are made in an entirely rational manner, which is not in line with current knowledge on the subject (Schmitz *et al.*, 2015). Therefore, the cognitive framework that also considers the non-rational factors of human behavior seems more interesting. In this group, the PECS (Physical conditions, Emotional states, Cognitive capabilities, and Social status) model is very popular (Urban and Schmidt, 2001). As its name implies, this model takes into account all factors that create its acronym.

When the agent-based simulation model considers the human factor, and the PECS behavioral framework is taken into account, some quality parameters, depending on the human's emotions or cognitive abilities, can be estimated from the neurophysiological data recorded using cognitive neuroscience techniques. They allow you to monitor both central and peripheral nervous systems (Kable, 2011). Changes in this activity, observed while performing specific tasks and activities, may become the basis for inferring about the examined individual's emotional or cognitive state (Vecchiato *et al.*, 2014). Thanks to this approach, the estimation of the qualitative parameters or variables can be significantly improved, as it relies not only on declarations on which conventional methods are based. The most used cognitive neuroscience techniques are presented in Table 1, broken down by methods used to study the central and peripheral nervous system's reactions, respectively.

Table 1. *Techniques of cognitive neuroscience for studying the reactions of the central and peripheral nervous system*

Central nervous system	Peripheral nervous system
– electroencephalography (EEG), – magnetoencephalography (MEG), – functional magnetic resonance imaging (fMRI), – functional near-infrared spectroscopy (fNIRS).	– galvanic skin response measurement (GSR), – heart rate measurement (HR), – breath measurement, – electromyography (EMG), – eye-tracking (ET), – face coding, – infrared thermography (IRT), – pupillometry.

Source: *Own elaboration.*

Research in many different science fields conducted using cognitive neuroscience techniques allowed to determine the occurrence of numerous emotional and cognitive states based on the analysis of collected neuro-physiological data. The relevant examples are summarized in Table 2.

Various types of emotions (especially those considered basic (Ekman, 1992)) are now effectively detected using EEG, EMG, eye-tracking and facial expression en-coding, MEG, fMRI, as well as using GSR and HR and respiration. In terms of cognitive states, the most numerous works focus on researching:
- memorization - by means of, among others, EEG and MEG,
- interest - research with the use of EEG,
- experiencing stress and relaxation - mainly using GSR and HR measurements,
- mental effort – using: EEG, fNIRS, GSR and thermography, HR measurements, eye-tracking and pupillometry.

Research to detect other emotional and cognitive states is still ongoing. Thanks to new discoveries in this field, many agent-based simulation models, considering the human factor, may significantly improve accuracy. One of such models is presented later in the article in terms of its applicability in an experiment allowing the estimation of a qualitative parameter's value using cognitive neuroscience techniques.

Table 2. *Emotional and cognitive states that can be detected with the use of cognitive neuroscience techniques*

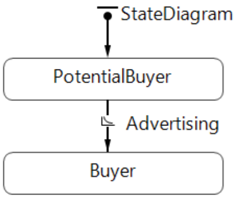
	Method	EEG	MEG	fMRI	fNIRS	GSR	HR	Breath	EMG	ET	Face coding	IRT	Pupillometry
Emotional or cognitive state	Emotional valence (emotions)	(Cipresso *et al.*, 2015)	(Yang and Lin, 2013)	(Greene, Flannery and Soto, 2014)	(Heger at al., 2014)	(Greco *et al.*, 2016)	(Rainville *et al.*, 2006)	(Rainville *et al.*, 2006)	(Cipresso *et al.*, 2015)	(Cipresso *et al.*, 2015)	(Cipresso *et al.*, 2015)	(Znamensk-aya *et al.*, 2018)	
	Engage-ment	(Mauri *et al.*, 2010)									(Whitehill *et al.*, 2014)		
	Memori-zation	(Fabiani, *et.al*,(2000)	(Osipova *et al.*, 2006)	(Talamonti *et al.*, 2020)						(Hannula *et al.*, 2010)			(Papesh *et al.*, 2012)
	Interest	(Vecchiato *et al.*, 2014)											
	Stress			(van Marle *et al.*, 2009)		(Mauri *et al.*, 2010)	(Mauri *et al.*, 2010)	(Mauri *et al.*, 2010)	(Pourmo-hammadi and Maleki, 2020)		(Dinges *et al.*, 2005)	(Kajiwara, 2014)	
	Relax					(Mauri *et al.*, 2010)							
	Cognitive load	(Borghini *et al.*, 2014)		(Jaeggi *et al.*, 2007)	(Asgher *et al.*, 2020)	(Kajiwara, 2014)	(Borghini *et al.*, 2014)		(Oschlies-Strobel *et al.*, 2017)	(Matthews *et al.*, 2018)		(Kajiwara, 2014)	(Čegovnik *et al.*, 2018)
	Attention	(Fabiani *et.al.*, 2000)	(Daliri, 2014)	(Parhizi *et al.*, 2018)				(Hasenkamp *et al.*, 2012)		(Shi *et al.*, 2017)		(Tag *et al.*, 2017)	(Zennifa and Iramina, 2019)
	Hidden intentions	(Kang *et al.*, 2015)		(Haynes *et al.*, 2007)									
	Esthetic prefere-nces	(Chew *et al.*, 2016)											
	Empathy			(Schnell *et al.*, 2011)									
	Motiva-tion			(Locke and Braver, 2008)									
	Moral decision making				(Balconi and Fronda, 2020)								

Source: *Own elaboration.*

4. Description of the Exemplary Model

A proposal for estimating a qualitative parameter based on data recorded using cognitive neuroscience techniques will be presented based on a product life cycle model, which can be used to forecast new products' sales. It is a model based on the classic Bass diffusion model, the characteristic feature of which is, confirmed by many applications, universality in forecasting the sales of newly introduced products belonging to various market segments. (Bass, 1969). The model maps the process of purchasing new products as an interaction between its current and potential users. Advertising encourages potential users to buy. The effectiveness of the ad in the model is determined by the value of the parameter named *AdAffectiveness*. It is the percentage of potential users who are ready to buy the product on a given day. The agents in the model are people - current and future users of the product. The state diagram for each of the agents in the model is presented in Figure 1.

Figure 1. *The agent state diagram in the diffusion model*



Source: *Own elaboration based on Grigoryev (2018).*

Each agent can be in one of two states - either he is a potential buyer of a given product or has already purchased it. The decision to buy depends on the *AdAffectiveness* parameter, which determines the agent's probability of moving from the *PotentialBuyer* state to the *Buyer* state.

In the classic version of the diffusion model, it is assumed that the probability that a person becomes interested in a product under the influence of advertising has a constant value. However, this is a significant simplification. In fact, the transition between states can be influenced by many different factors - most notably those related to the individual characteristics of the audience of an advertising message. Therefore, to improve the model, one should take these factors into account. The previously mentioned qualitative and quantitative methods of estimating model parameters can be used to make it possible. To obtain the complete picture of the situation, it is also worth considering the possibilities of cognitive neuroscience techniques. A proposal for an experiment that allows us to estimate the *AdAffectiveness* parameter through triangulation of diagnostic survey methods and cognitive neuroscience is presented later in the article.

5. Experiment Design

The described project of the experiment aims to estimate the value of the *AdEffectiveness* parameter using the techniques of cognitive neuroscience. The choice of this element is dictated by the fact that in numerous studies published in the literature on the subject, the effectiveness of various types of advertising has already been repeatedly assessed based on neurophysiological data (Langleben *et al.*, 2009; Vecchiato *et al.*, 2010; Vecchiato *et al.*, 2014; Deitz *et al.*, 2016; Barnett and Cerf, 2017; Ciceri *et al.*, 2020). Among the cognitive and emotional states that can be detected with neuroscience research tools, the presented stimuli' interest is determined based on the so-called frontal asymmetry. It is expressed using the so-called approach-withdrawal index (AW) described by the formula (Davidson, 2004; Vecchiato *et al.*, 2014):

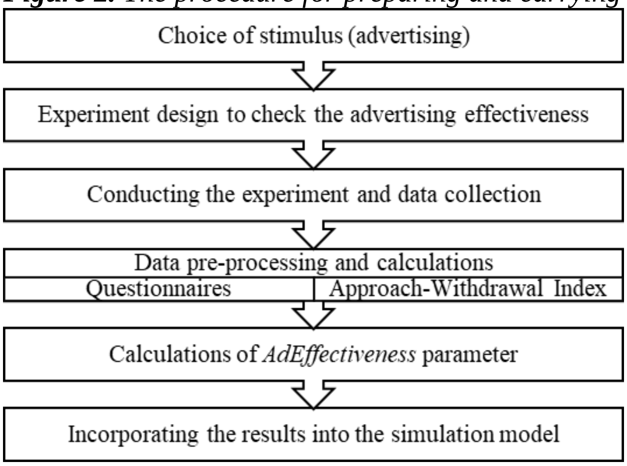
$$AW = \frac{1}{\mathrm{N_P}}\sum_{\mathrm{i\in P}} \mathrm{x}^2_{\alpha_\mathrm{i}}(t) - \frac{1}{\mathrm{N_Q}}\sum_{\mathrm{i\in Q}} \mathrm{y}^2_{\alpha_\mathrm{i}}(t) = Average\ Power_{\alpha_{right,\mathrm{frontal}}} - \mathrm{Average\ Power}_{\alpha_{\mathrm{left,frontal}}} \tag{1}$$

where:

$\mathrm{x}_{\alpha_\mathrm{i}}$ and $\mathrm{y}_{\alpha_\mathrm{i}}$ – *i*-th EEG channel in the alpha band (right and left frontal lobes, respectively),
P and *Q*– sets of right and left channels,
N_P and N_Q – cardinality of *P* and *Q*

The proposed experiment will be prepared and carried out in accordance with the procedure presented in Figure 2.

Figure 2. *The procedure for preparing and carrying out the experiment*



Source: *Own elaboration.*

In the basic version, the presented diffusion model is very general – it can apply to any product sold on the market. However, applying the proposed approach to estimate the *AdEffectiveness* parameter requires, first of all, to decide which product or possibly a group of products will be the subject of the model. This decision is necessary to select the appropriate ads for the experiment. Next, you should define how the chosen ads will be presented to participants (whether it will be a static image or a video) and how many stimuli will be taken into account (how many ads will be displayed during one experimental session). Due to the selected measure (approach-withdrawal index), the registration of neurophysiological data in the experiment will be performed only using EEG. To make the obtained results more reliable, parallel to the signals of neural activity, data will also be collected from questionnaires on the evaluation of advertisements and their effectiveness in the opinion of participants of the experiment. This approach is recommended in the literature (Glimcher and Rustichini, 2004; Vecchiato *et al.*, 2013).

The questionnaire and EEG registration results should be finally aggregated to get the final parameter value that could be included in the diffusion model. The proposed method of aggregating the obtained data to estimate the model's *AdEffectiveness* parameter is presented in Table 2.

Table 2. *The method of aggregation to estimate the AdEffectiveness parameter value*

	EEG data	Questionnaire data
Results for individual participant	Normalized numerical value calculated according to the formula for each second of the stimulus presentation and then averaged for the entire duration of the advertisement	A numerical value representing the subjective ad effectiveness on the Likert scale
Results for a group of participants	The arithmetic mean of the results recorded for individuals	The arithmetic mean of assessments from individual persons
Value of the parameter *AdEffectiveness*	The arithmetic mean of the values obtained for the EEG data and questionnaires	

Source: *Own elaboration.*

6. Conclusions

Estimating agent-based simulation models' parameters considering the human factor is a complex and time-consuming task. For the model to accurately reflect reality, numerous methods are used to collect information on the examined microprocesses. The most frequently used methods include those representing a quantitative approach, mainly in the form of questionnaires. They are easy to apply but have significant drawbacks. The imperfection of such an approach manifests itself, especially when the model tries to take into account also behavioral factors, such as in the case of modeling consumer behavior, according to the PECS model. It considers, among other things, such elements as the emotional and cognitive states of agents. This prompts us to take steps to supplement the questionnaire data with neurophysiological data.

Research in the field of cognitive neuroscience already allows for reasonably accurate recognition of various types of conditions that may directly affect the behavior of the model's agents. Examples of such states are presented in the articles. One of them - interest - was used to present the concept of estimating the value of an exemplary diffusion model parameter using the triangulation of cognitive neuroscience methods and a diagnostic survey. The project of the experiment was also presented, which will allow for the implementation of the entire procedure of estimating the value of the qualitative variable *AdEffectiveness*. The next step in the research will be to carry out the proposed experiment and verify the proposed approach with regard to determining the value of parameters and validating the model.

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